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Forecasting bitcoin price fluctuations: a time series analysis approach for predictive modelling

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ABSTRACT

The recent fluctuations in the price of Bitcoin, marked by both significant increases and subsequent decreases, has attracted media and public attention. Consequently, many researchers have explored various factors influencing Bitcoin's price and the underlying patterns of its fluctuations. This paper aims to predict and analyses the factors affecting Bitcoin's price by creating a unique dataset with nearly 40 features and deriving two child datasets using correlation and mutual information as feature selection techniques. Additionally, we train machine learning models, including linear regression (LR), extreme gradient boosting (XGBoost), support vector regression (SVR), Facebook Prophet (FB Prophet), and bidirectional gated recurrent unit (BI-GRU), to predict Bitcoin's next-day price. The model's performance is evaluated using mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and R2 score metrics. Our findings indicate that machine learning techniques are effective in predicting Bitcoin's price and could be valuable for investors seeking to maximize profits.

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1. INTRODUCTION

Bitcoin, established as a decentralized digital currency in 2008 by the pseudonymous figure Satoshi Nakamoto, revolutionized the financial landscape with its innovative framework outlined in the paper titled "Bitcoin: a peer-to-peer (P2P) electronic cash system" [1]. As a cryptocurrency, Bitcoin relies on cryptographic techniques for security [2], operates independently of governmental or financial control, and has become renowned for its inherent volatility [3], [4]. The primary challenge in predicting Bitcoin prices lies in its market dynamics, characterized by rapid and substantial price movements within short time frames. As a relatively new and volatile asset class, Bitcoin's price forecasting is complicated by numerous factors, including technological advancements, government support and regulation [5], socioeconomic changes [6], shifts in investor sentiment [7], and the impact of events like the COVID-19 pandemic [8], [9].

In the domain of cryptocurrency market prediction [10], both deep learning and traditional machine learning models have been employed. Significant contributions include multi-layer perceptrons (MLPs) [11], which have demonstrated success in capturing complex patterns in data, convolutional neural networks (CNNs), known for their effectiveness in character recognition and text classification [12]-[14] and recurrent neural networks (RNNs), with their variants LSTM and GRU [15], [16], which are proficient in modeling time-dependent data, as well as combinations of CNN and LSTM [17]. Traditional machine learning models, such as linear regression (LR), support vector regression (SVR), and extreme gradient boosting (XGBoost) [18], offer robust performance and are often easier to interpret. Additionally, time series forecasting methods like auto regressive integrated moving average (ARIMA), auto regression (AR), and moving average (MA) [19], as well as Facebook Prophet (FB Prophet), have been applied to predict cryptocurrency prices [20], [21].

Despite these advancements, predicting Bitcoin prices remains a significant challenge due to the complexity and volatility of the market. Existing models often fail to account for the multifaceted factors influencing Bitcoin prices. There is a need for a comprehensive model that integrates a wide range of variables to improve prediction accuracy.

This research aims to develop an accurate and reliable model for predicting Bitcoin prices by compiling data from diverse domains that influence Bitcoin's price movements. These domains include Bitcoin-specific variables (open, high, close, and low), technological aspects of Bitcoin cryptocurrencies, market features, commodities, public recognition, geopolitical factors, and market sentiment indexes, along with technical indicators. By integrating these factors into a comprehensive dataset, we seek to capture the complexity of Bitcoin price dynamics more effectively than previous models. The following sections will demonstrate the methodology used to gather and preprocess the data, the model development process, and the evaluation of the model's performance. The results will be discussed in the context of their relevance to the field, highlighting how our approach addresses the limitations of previous works and contributes to the advancement of cryptocurrency price prediction models.

2. METHOD

This section presents the methodology used in this study, as illustrated in Figure 1. The primary objective is to develop an accurate predictive model for forecasting Bitcoin prices. To accomplish this, the study combines historical data analysis from diverse fields and domains, systematic data preprocessing, feature selection techniques, machine learning algorithms, and performance evaluation metrics. These steps are designed to ensure the model's reliability and improve its predictive accuracy.

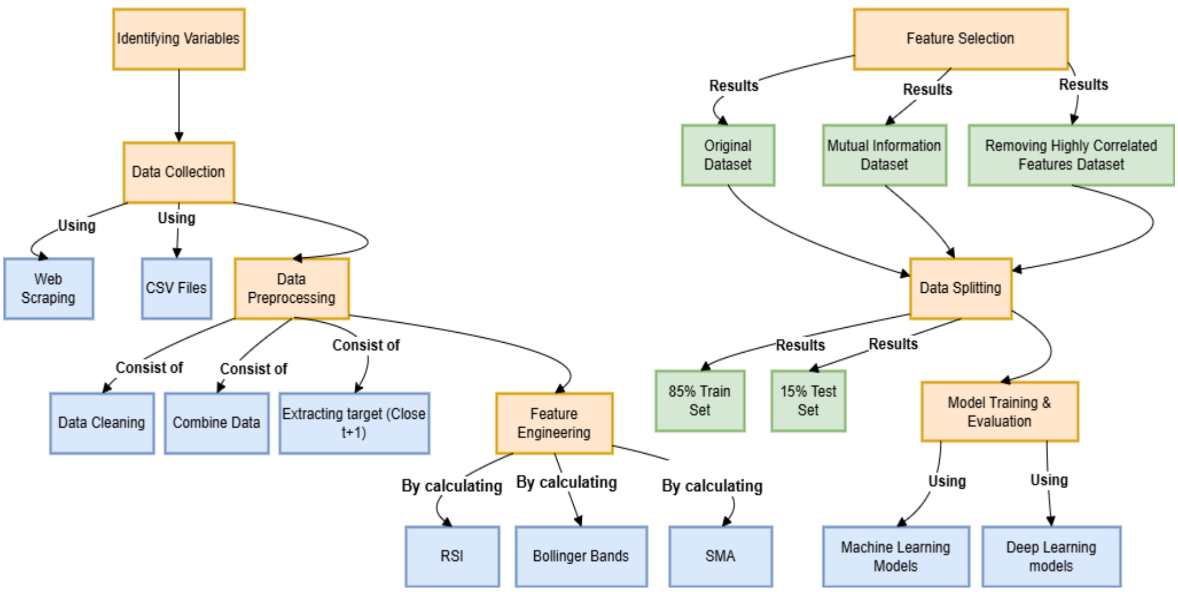


Figure 1. Followed process in methodology

2.1. Identifying variables

The initial step is to identify variables that can have a significant impact on Bitcoin's price. Bitcoin blockchain metrics, market uncertainty indexes and geopolitical risk measures are all important. These features have been identified as probable drivers of Bitcoin price variations, and they serve as the foundation for developing an effective forecasting model. The Table 1 groups all the features used in the study.

Table 1. Features and descriptions

Features	Definitions
Open	The initial price of Bitcoin at the beginning of trading session.
Close	The final price of Bitcoin at the end of a trading session.
High	The maximum value of Bitcoin price in during a trading period.
Low	The minimum value of Bitcoin price in during a trading period.
Cryptocurrency market capitalization	The aggregate worth of all cryptocurrencies in USD.
Bitcoin market capitalization	The total monetary value of all Bitcoins in circulation in USD.
Cryptocurrency market capitalization excluding Bitcoin	The aggregate worth of all cryptocurrencies excluding Bitcoin in USD.
Volume	The total quantity of bitcoins traded during a trading period.
Change	The daily percentage change in the worth of Bitcoin.
Bitcoin dominance	The percentage of the total cryptocurrency market capitalization that is represented by Bitcoin.
Ethereum dominance	The percentage of the total cryptocurrency market capitalization that is represented by Ethereum
Active Cryptocurrencies	The number of active or widely traded cryptocurrencies.
Number of transactions	The number of Bitcoin transactions each day.
Mining difficulty	The difficulty of mining a new block on the Bitcoin blockchain.
Hashrate	The average computing power used to mine Bitcoin daily.
Transactions fees	The average daily cost of Bitcoin transactions.
Transaction value	The average value in dollars of Bitcoin transactions every day.
Sent coin in USD	Coin was sent in USD per day.
Miners' revenue	The total amount of money earned by the miners of Bitcoin when confirming transactions.
Number of bitcoins in circulation	The total number of bitcoins in exchange and use.
Relative strength index	Determines whether a financial asset is overbought or oversold by measuring the size of recent price fluctuations
Bollinger bands (Upper/Middle/Lower)	Determine the levels of potential support and resistance of an asset's price
Smooth moving average	Used for identifying price trends in financial instruments
Geopolitical risk index USA [22]	An indicator that quantifies the impact of political and economic risk to a country's stability and investment in global markets.
Economic policy uncertainty index USA [23]	An index that measures the level of uncertainty surrounding economic policy, which influences investment decisions and economic performance.
Consumer price index [24]	A measure of average price increases in a basket of goods and services purchased by families, indicating the rate of inflation.
Gold price	Current market value of an ounce of gold in USD.
Oil price	The current global market price of west Texas intermediate (WTI) crude oil, a benchmark for oil prices.
Twitter/Google trend	Bitcoin Twitter and Google Trends refer to the public interest on Bitcoin expressed through Twitter mentions and Google searches.
Twitter market uncertainty in English	A measure of market uncertainty developed from Twitter data and sentiment analysis of tweets.
Twitter economic uncertainty in English [25]	The economic uncertainty index is derived from Twitter data, and it reflects sentiments and talks about economic conditions and uncertainties.
COVID-19 new death/case	The term "COVID-19 new deaths" refers to the number of newly reported COVID-19 deaths, whereas "COVID-19 new cases" refers to the number of newly reported COVID-19 infections.

2.2. Data collection

A dual approach is adopted to collect the necessary data for the identified variables. The first method involves gathering data from CSV files, which provides structured and readily available information for analysis. The second method utilizes web scraping techniques, implemented through Python libraries such as beautiful soup and requests, to extract data from online sources. By employing these methods, the study ensures the availability of high-quality data for subsequent preprocessing and analysis.

2.3. Data pre-processing

To maintain the quality and consistency of the collected data, a thorough data cleaning process is conducted. This process identifies and corrects any anomalies, missing values, or errors in the data to ensure its reliability for further analysis. Additionally, separate data series are merged into a single unified dataset, with timestamps aligned to create a consistent time series format. The Python library Pandas is used for this integration, enabling efficient handling and manipulation of the data. By performing these steps, the study ensures that the dataset is both accurate and ready for subsequent analytical procedures.

2.4. Feature engineering

Feature engineering is the practice of extracting additional features from an existing dataset in order to improve the predictive modeling process. Technical indicators such as the relative strength index (RSI), Bollinger Bands (BBands), and simple moving average (SMA) are computed in this study by the help of

Pandas-Ta library. By incorporating RSI, BBands, and SMA into the study we ensure a comprehensive analysis of market conditions, combining momentum, volatility, and trend indicators to enhance the predictive performance of the Bitcoin price forecasting model.

2.5. Feature selection

Feature selection is a significant phase in refining the dataset and optimizing model performance, for identifying and preserve the most significant attributes, we employ two filter feature selection methods: correlation-based and mutual information-based to evaluate features based on their statistical properties or their relationships with the target variable, independent of any specific machine learning algorithm. The correlation-based method to minimizes multicollinearity and potentially increases model interpretability by removing pairs of features with a high correlation coefficient, specifically those above a threshold of 0.85. The mutual information method, implemented using Scikit-learn's 'mutual_info_regression' involves calculating the score between each feature and the target variable, then selecting the features with the highest mutual information scores to ensure that only the most informative features are included, which can significantly enhance the model's ability to make accurate predictions.

2.6. Data normalization and splitting

After, cleaning data and handling missing values a minimum and maximum scaler (MinMaxScaler) has been applied for each dataset. Thus, all the variables are unified between 0 and 1, the scaling formula presented in (1). As illustrated in Figure 2, the dataset will be partitioned into training and test sets, with 85% (3025 days) designated for training from April 30, 2013, to August 10, 2021, and 15% (534 days) allocated for testing spanning August 11, 2021, to January 26, 2023.

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

2.7. Training and evaluation

Training was conducted for each model on the original dataset as well as the two derived datasets created through feature selection. We began with machine learning models, including XGBoost, LR, SVR and FBProphet. Additionally, we developed a deep learning model using TensorFlow based on RNN variants, specifically Bi-GRU, Figure 3 shows our proposed model architecture. Then we assess the models' performance using mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), and R2 score. These metrics offer a thorough evaluation of the model's predictive precision and resilience. The formulas for computing these metrics are provided in (2) through (4). The specific configurations for each model are outlined in Table 2.

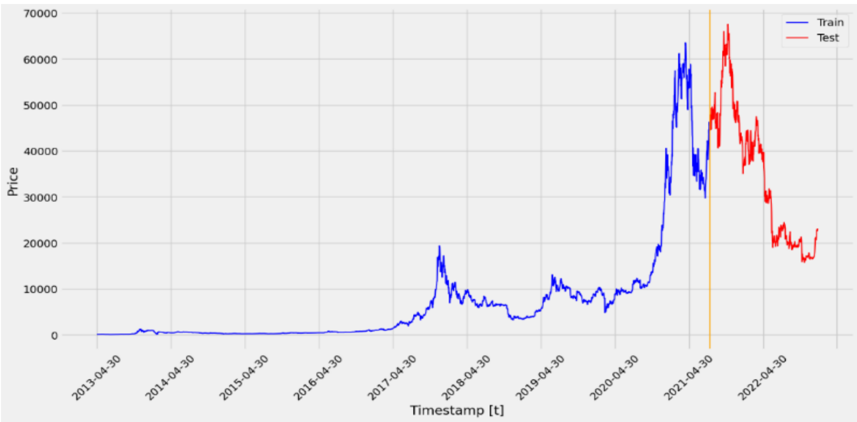


Figure 2. Training and testing splits

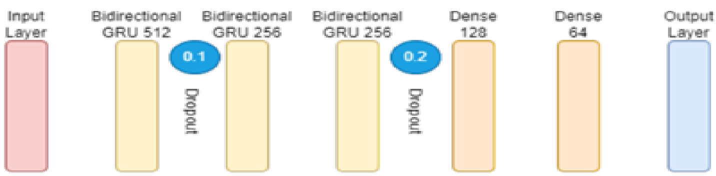


Figure 3. Bi-GRU model architecture

Table 2. Model libraries and configurations

Model	Library	Configuration
LR	Scikit-learn	Default parameters
SVR	Scikit-learn	C= 10, epsilon= 0.01, kernel= ‘linear’
XGBoost	xgboost	booster= ‘gblinear’, n_estimators= 10,000, objective=‘reg:squarederror’
FbProphet	prophet	We added a regressor for every feature in the dataset
Bi-GRU	TensorFlow	loss= ‘mean_squared_error’, optimizer= ‘adam’, metrics= ‘mae’, look_back = 7, epochs = 100, batch_size = 128, and a linear activation for dense layers

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right| \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2 \quad (4)$$

$$R2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \quad (5)$$

3. RESULTS AND DISCUSSION

After initiating the study by collecting and pre-processing the data and consolidating it into a single dataset, we proceed with feature engineering by calculating several technical indicators. These include the SMA over 20 periods, the RSI over 14 periods, and the BBands over 20 periods. This enhances the dataset by incorporating valuable market indicators that can aid in predicting Bitcoin prices.

Following this, we apply feature selection techniques correlation and mutual information, scores are provided in Figures 4 and 5 respectively. As a result, two additional datasets are derived from the original dataset, each containing a unique set of selected features. Table 3 outlines the specific features chosen for each of the resultant datasets, highlighting the differences and the rationale behind the selection in each case. The mutual information technique selected features such as open, volume, change, BTC dominance, and COVID-19 new cases among others, indicating these variables strong individual contributions to price prediction. In contrast, the method of removing highly correlated features resulted in the selection of different variables like high, low, Ethereum dominance, and total market capitalization highlighting the importance of minimizing redundancy and multicollinearity.

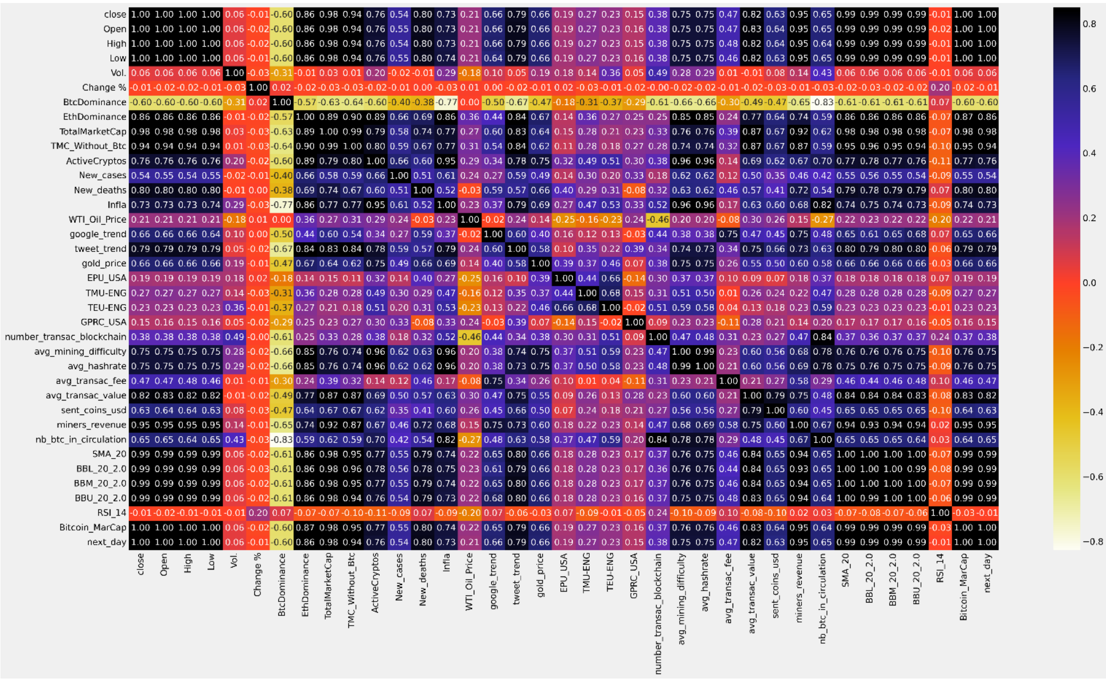


Figure 4. Correlation matrix score

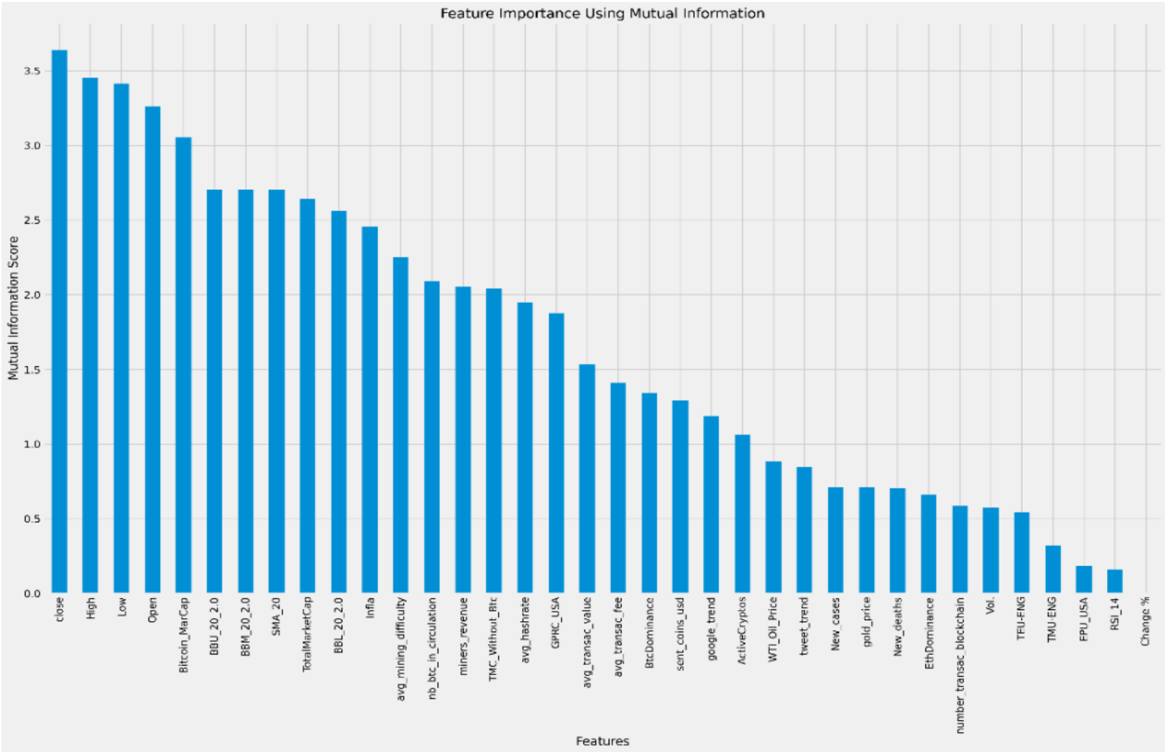


Figure 5. Mutual information score

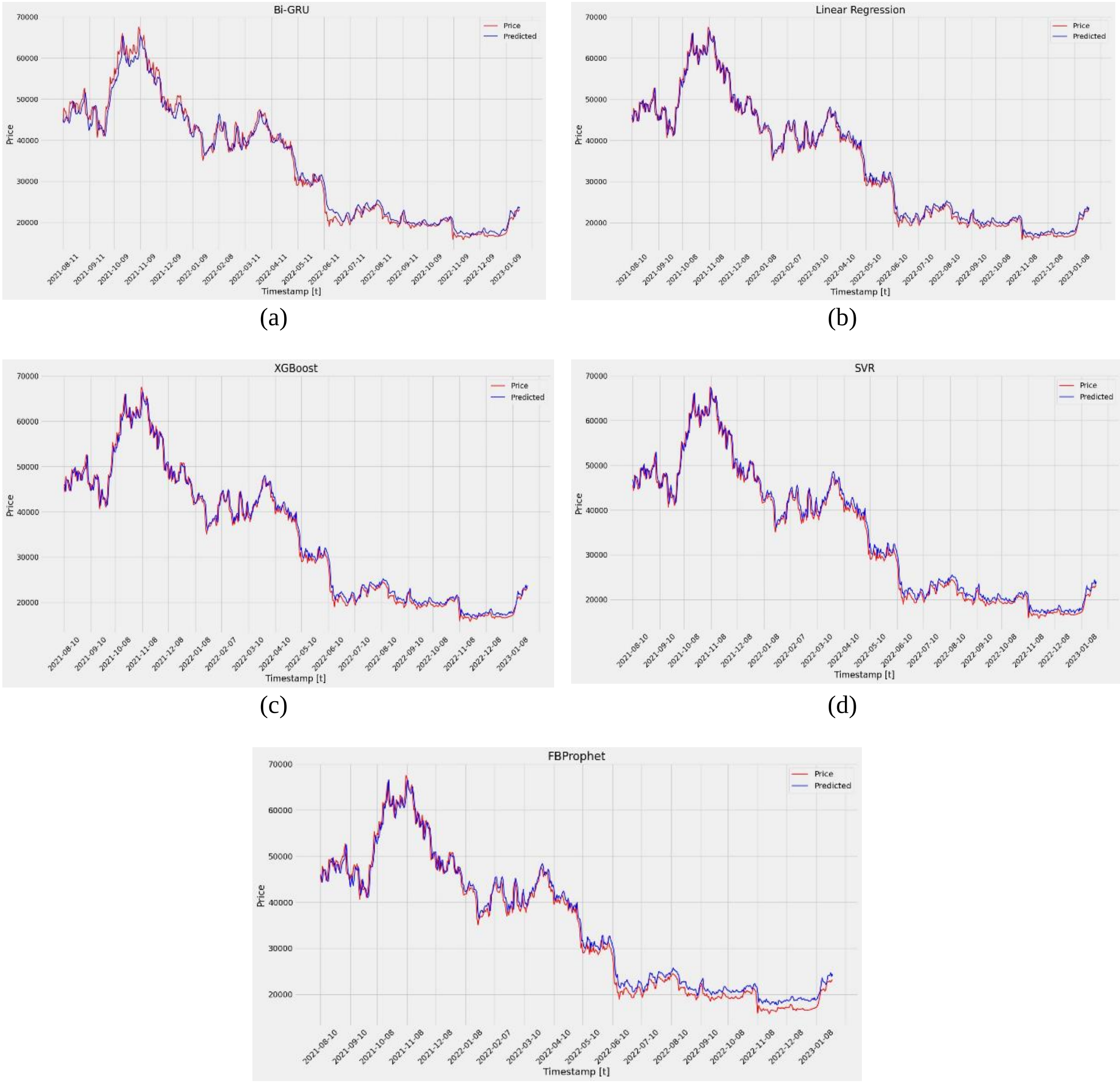
Table 3. Features extracted in each child dataset

Selected features using correlation (18 features)	Selected features using mutual information (19 features)
Open, volume, change, BTC dominance, COV19 new cases, COV19 new deaths, WTI oil price, Google trend, tweet trend, gold price, EPU, TMU, TEU, GPRC, number of transactions in blockchain, AVG transaction fee, sent coins in USD, number of BTC in circulation	Open, high, low, ethereum dominance, total market capitalization, total market capitalization without BTC, active cryptocurrencies, COV19 new deaths, CPI, tweet trend, AVG mining difficulty, AVG hashrate, AVG transaction value, miner's revenue, SMA, BBL, BBM, BBU, bitcoin market capitalization

The performance evaluation of Bitcoin price prediction models on the original dataset, as detailed in Table 4 and illustrated in Figure 6, includes the following models: Bi-GRU, LR, XGBoost, SVR, and FBProphet, highlights notable variations in performance. Starting with Bi-GRU, the model achieves a high R2 score of 0.9850 but slightly higher MAE (0.019) and MSE (0.0006), indicating moderate errors. Figure 6(a) shows good alignment between predicted and actual prices, though minor deviations are visible. LR performs well with an R2 score of 0.9894, MAE of 0.021, and MSE of 0.0006, with Figure 6(b) displaying close overlaps of predicted and actual prices, suggesting reliable predictions. XGBoost emerges as the most accurate model, achieving the highest R2 score of 0.9899 and the lowest errors (MAE of 0.020 and MAPE of 3.33%). Figure 6(c) illustrates minimal discrepancies between predicted and actual prices, indicating exceptional performance. SVR also delivers strong results, with an R2 score of 0.9884 and MAPE of 3.83%, as reflected in the Figure 6(d) closely matched price lines, though with slightly larger errors compared to XGBoost. Finally, FBprophet achieves reasonable accuracy with an R2 score of 0.9843 but exhibits higher MAPE (5.14%), as Figure 6(e) shows more pronounced deviations between predicted and actual values, especially during periods of high volatility. Overall, the models, particularly XGBoost, showcase promising results in forecasting Bitcoin prices, emphasizing the effectiveness of machine learning approaches in this context.

Table 4. performance metrics on mother dataset

Model	MAE	MSE	MAPE	R2 score
Bi-GRU	0.019	0.0006	4.09%	0.9850
XGBoost	0.020	0.0007	3.33%	0.9899
SVR	0.022	0.0008	3.83%	0.9884
LR	0.021	0.0007	3.54%	0.9894
FBprophet	0.021	0.0006	5.14%	0.9843



(a) (b)

(c) (d)

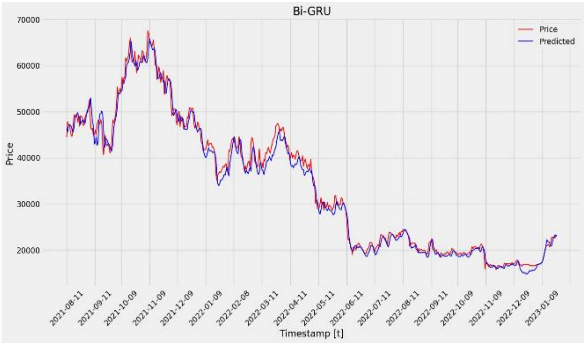
(e)

Figure 6. Models results on mother dataset; (a) Bi-GRU, (b) LR, (c) XGBoost, (d) SVR, and (e) FBProphet

The evaluation of Bitcoin price prediction models after applying a feature selection technique that removes highly correlated variables reveals improved performance, as summarized in Table 5 and illustrated in Figure 7 comprises the models Bi-GRU, LR, XGBoost, SVR, and FBProphet. Starting with Bi-GRU, the model delivers strong results with an R2 score of 0.9872, MAE of 0.017, and MAPE of 3.46%. Figure 7(a) demonstrates good alignment between predicted and actual prices, though minor discrepancies are visible, especially during volatile periods. LR performs exceptionally well, achieving the highest R2 score of 0.9920, MAE of 0.016, and the lowest MAPE of 2.52%. Figure 7(b) reveals near-perfect overlap between predicted and actual prices, highlighting its reliability. XGBoost matches LR in performance, also achieving an R2 score of 0.9920, MAE of 0.016, and a slightly higher MAPE of 2.53%. Figure 7(d) confirms exceptional predictive accuracy with minimal deviations. SVR follows closely with an R2 score of 0.9908, MAE of 0.020, and MAPE of 3.50%. While Figure 7(c) reflects robust alignment, it shows slightly larger deviations compared to XGBoost and LR, particularly during high price fluctuations. Finally, FBprophet achieves the lowest MAE (0.015) and MSE (0.0004), along with an R2 score of 0.9903 and a MAPE of 3.14%. Figure 7(e) illustrates strong alignment between predictions and actual values, though some discrepancies are observed during volatile periods. The removal of highly correlated features appears to enhance all models' performance, as reflected in reduced errors and consistently high predictive reliability across the board, emphasizing the effectiveness of feature selection in refining Bitcoin price forecasting.

Table 1. Performance metrics on correlation dataset

Model	MAE	MSE	MAPE	R2 score
Bi-GRU	0.017	0.0005	3.46%	0.9872
XGBoost	0.016	0.0006	2.53%	0.9920
SVR	0.020	0.0007	3.50%	0.9908
LR	0.016	0.0006	2.52%	0.9920
FBprophet	0.015	0.0004	3.14%	0.9903



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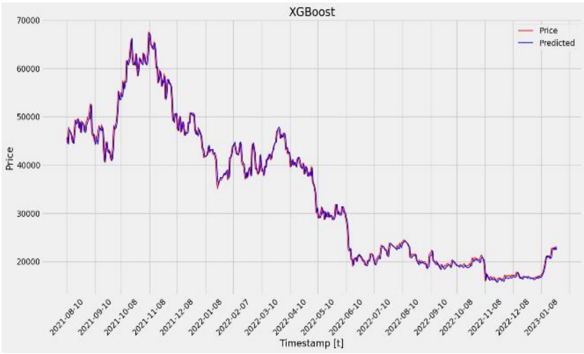

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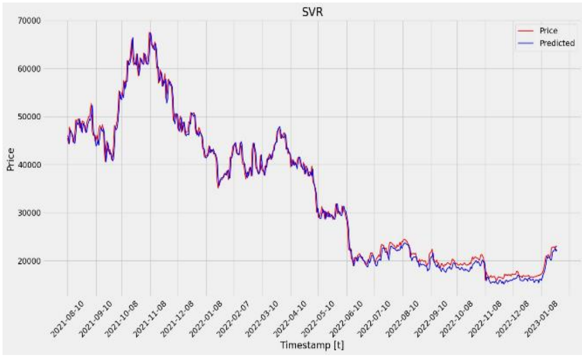

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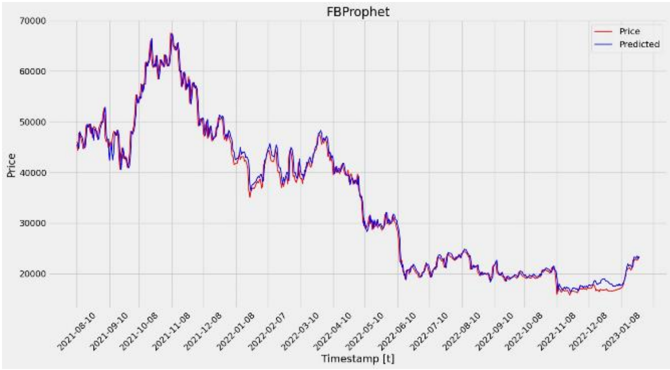


(e)

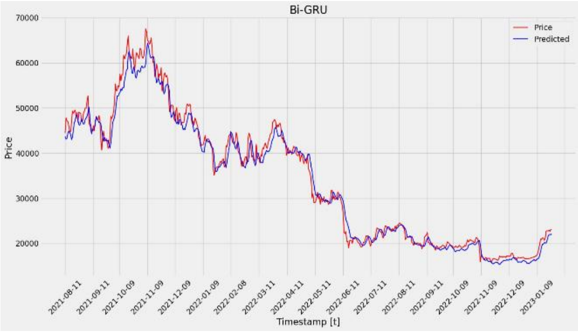
Figure 7. Model results on correlation dataset; (a) Bi-GRU, (b) LR, (c) XGBoost, (d) SVR, and (e) FBProphet

The analysis of Bitcoin price prediction models using mutual information as a feature selection technique provides valuable insights, as illustrated in Table 6 and Figure 8 consists of the models Bi-GRU, LR, XGBoost, SVR, and FBProphet. Beginning with Bi-GRU, the model achieves an R2 score of 0.9821, MAE of 0.020, and MAPE of 4.12%. Figure 8(a) highlights good alignment between predicted and actual prices, though some deviations are visible during volatile periods. LR performs exceptionally well with the highest R2 score of 0.9919, MAE of 0.016, and the lowest MAPE of 2.45%. Figure 8(b) shows near-perfect overlap between predicted and actual prices, emphasizing its predictive accuracy. XGBoost closely matches

LR, achieving an R2 score of 0.9918, MAE of 0.016, and a slightly higher MAPE of 2.47%. Figure 8(c) confirms the model's exceptional precision, with minimal deviations. SVR also delivers strong performance, with an R2 score of 0.9910, MAE of 0.017, and MAPE of 2.53%. Figure 8(d) reflects robust alignment between actual and predicted prices, though it shows slightly larger errors compared to LR and XGBoost. Finally, FBprophet achieves an R2 score of 0.9846, MAE of 0.020, and MAPE of 5.20%. Figure 8(e) demonstrates reasonable alignment but shows more pronounced deviations, especially during periods of high volatility. Mutual information as a feature selection method proves beneficial, enhancing the predictive accuracy of all models and reaffirming its value in optimizing Bitcoin price forecasting.

Table 6. Performance metrics on mutual information dataset

Model	MAE	MSE	MAPE	R2 score
Bi-GRU	0.020	0.0008	4.12%	0.9821
XGBoost	0.016	0.0006	2.47%	0.9918
SVR	0.017	0.0006	2.53%	0.9910
LR	0.016	0.0006	2.45%	0.9919
FBprophet	0.020	0.0006	5.20%	0.9846



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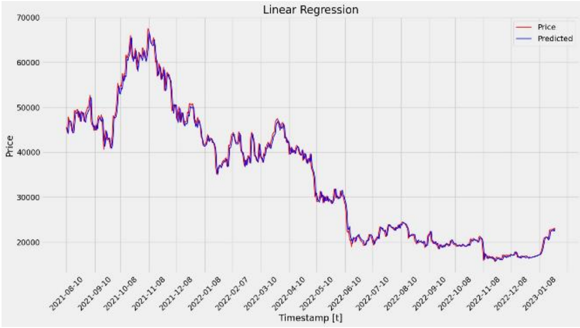

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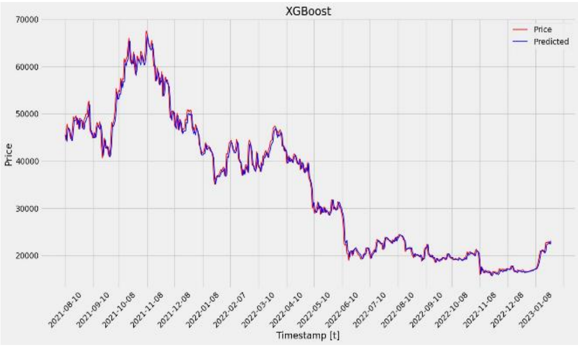

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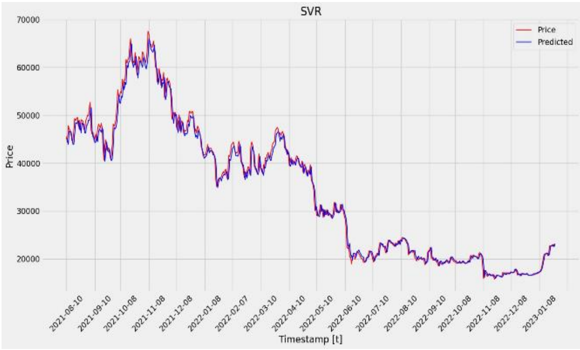

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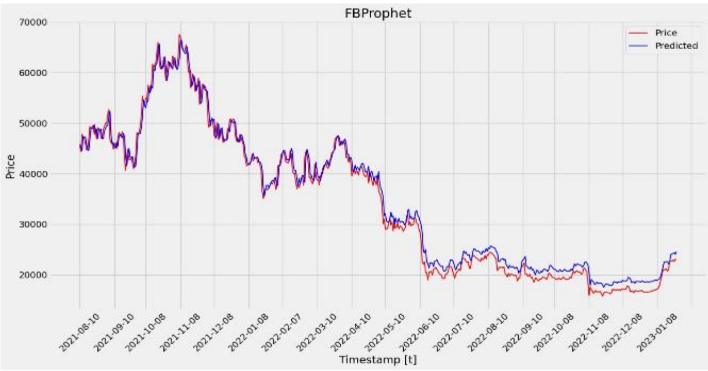

(e)

Figure 8. Model results on mutual information dataset; (a) Bi-GRU, (b) LR, (c) XGBoost, (d) SVR, and (e) FBProphet

This study investigated the predictive performance of machine learning models, particularly their effectiveness in forecasting Bitcoin prices. While previous research has demonstrated the potential of machine learning models in the cryptocurrency domain, they have often overlooked the impact of integrating multiple economic and geopolitical factors, such as EPU, TMU, TEU, and GPRC. Additionally, there has been limited focus on how the removal of highly correlated variables within feature sets might enhance model accuracy.

Our findings indicate that the XGBoost model consistently outperformed other models in predicting Bitcoin prices, as reflected by its lower MAE and MSE across various datasets and feature selection techniques. Consolidating key economic indicators into a single dataset, coupled with the removal of highly correlated features, significantly improved the model's predictive accuracy. Interestingly, while the Bi-GRU model exhibited slightly higher MAE and MSE values than XGBoost, it still achieved a strong R2 score, demonstrating its potential for capturing temporal dependencies in volatile Bitcoin data.

When comparing our results to prior studies, it becomes clear that machine learning models continue to be highly effective in predicting cryptocurrency prices. Like earlier research, our study confirms that incorporating multiple factors into the feature selection process can substantially improve model performance. However, a key distinction in our work is the emphasis on removing highly correlated features, which, unlike in some previous studies, proved to significantly enhance the accuracy of the predictions. This suggests that careful feature selection is particularly important when dealing with complex, volatile markets like cryptocurrencies.

One limitation of our study is the reliance on historical data, which may not fully account for future market anomalies or sudden shifts in market conditions. This could limit the model's effectiveness in real-time scenarios, where market dynamics are constantly evolving. Furthermore, unexpected findings such as the high performance of the Bi-GRU model, despite its relatively higher MAE and MSE compared to XGBoost, warrant further investigation. These results indicate that deep learning models like Bi-GRU may have potential in capturing patterns over time in Bitcoin price movements.

Looking forward, future research could focus on incorporating real-time data to evaluate the model's ability to respond to market shocks and external events. Additionally, exploring more advanced deep learning models, such as Bi-GRU, may provide deeper insights into capturing temporal dependencies in volatile markets. The integration of real-time market data and the exploration of sudden market fluctuations are crucial steps for advancing predictive modeling in cryptocurrency markets.

In summary, our study demonstrates that the XGBoost model excels in predicting Bitcoin prices, particularly when robust feature selection techniques are applied. The removal of highly correlated features, along with the integration of diverse market indicators, significantly improves model performance. However, the integration of real-time data and an understanding of model responses to market shocks are important areas for future research.

4. CONCLUSION

In conclusion, this study explored the effectiveness of various factors in predicting Bitcoin prices. To achieve this, we developed a unique dataset comprising nearly 40 features from different domains. Using filter methods for feature selection, we derived two additional datasets from the original one. We then applied several machine learning models, including XGBoost, SVR, LR, and FBProphet, as well as a deep learning model based on Bi-GRU, to analyze their capability to capture price movement patterns. Our results demonstrated that XGBoost and LR consistently outperformed other models, showing the lowest error values across all datasets. This indicates their superior ability to predict Bitcoin prices accurately. Additionally, we found that utilizing Correlation and Mutual Information as feature selection techniques effectively reduced the error rates of the models. This highlights the importance of feature selection in enhancing model performance. Future research could benefit from exploring specialized time series forecasting models, such as TimesNet, NBEATS, and N-HITS, to further improve prediction accuracy. These models are specifically designed to handle time series data and could provide deeper insights into the patterns and trends underlying Bitcoin price movements. Moreover, integrating more advanced machine learning and deep learning techniques, as well as considering additional external factors and the integration of real-time data, could further refine the predictive models and contribute to the growing field of cryptocurrency market prediction.

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